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Modeling Water-Stressed Cotton Growth Using Within-Season Remote Sensing Data

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ABSTRACT

Remotely sensed crop reflectance data can be used to simulate crop growth using within-season calibration. A model based on GRAMI, previously modified to simulate cotton (*Gossypium hirsutum* L.) growth, was revised and tested to simulate leaf area development and to estimate lint yield of water-stressed cotton. To verify the model, cotton field data, such as leaf area index (LAI), lint yield, and remotely sensed vegetation indices (VI), were obtained from an experimental field treated with various irrigation levels at the Plant Stress and Water Conservation Laboratory at Lubbock, Texas from 2002 to 2004. The model was validated using field data obtained separately from verification data at the same location in 2005. A hand-held multispectral radiometer with 16 spectral bands was used to measure reflectance. Five VI designs of interest were evaluated and used as input values for within-season calibration of the model. Simulated VI and LAI were in agreement with the measured VI and LAI, with r^2 values from 0.96 to 0.97 and RMSE values from 0.02 to 0.24 in validation. Simulated lint yields were in agreement with measured lint yields, with r^2 values from 0.63 to 0.67 and RMSE values from 28.3 to 100.0. The model was not very sensitive to the higher irrigation treatments in reproducing lint yield. We believe that validation with more data sets can deal with this matter. The VI worked equally well in reproducing measured cotton growth when they were used for within-season calibration. The results of this calibration scheme suggest that remote sensing data could be used to adjust modeled cotton growth for various water-stressed conditions.

In the course of the development and use of crop growth models, there have been many attempts to improve their accuracy and usability. To improve the general ability of crop models to simulate crop growth, some modelers have attempted to make model parameters adjustable so that simulation can agree with observation. In one of the earliest attempts, Arkin et al. (1977) proposed the concept of a hybrid "spectral-physiological" model able to use Landsat data. This concept was described in the model SORGF (Maas and Arkin, 1978). Some of the efforts that followed were the models of SOYGRO (Wilkerson et al., 1985) and SORKAM (Rosenthal et al., 1989). Users of SOYGRO can adjust a parameter affecting photosynthesis rate to improve agreement between simulated and measured biomasses. In SORKAM, a parameter affecting leaf expansion rate can be adjusted to make agreement between simulated and measured leaf area index (LAI). More recently, Barns et al. (1997) modified CERES-Wheat (Ritchie and Otter, 1985) to allow the model to accept observed LAI and to adjust related parameters in the model as a function of LAI. Although these procedures objectively calibrate model response to actual field conditions for each application of the model, they require the acquisition of the same input requirements that CERES-Wheat requires. Recently, Baez-Gonzalez et al. (2002) reported a method using satellite and field data with crop growth modeling to monitor and estimate corn yield. They showed that a crop model integrated with satellite imagery and field data can be used to monitor crop growth and to assess grain yield on a large scale.

Within-season calibration is one of the procedures used to improve the accuracy of model estimates using relatively simple input requirements (Maas, 1993b). In this calibration method (see Fig. 2), actual measurements of crop leaf area development are obtained at specified stages of the growing season. Certain parameters and initial conditions of the model are then iteratively adjusted until the resulting simulated crop growth achieves a best fit to the actual state of the crop at those stages of growth. This methodology was originally implemented in GRAMI, a model for estimating the growth and yield of grain crops (Maas, 1992 and 1993b). The methodology was used to estimate evaporation and biomass production (Moran et al., 1995; Maas and Doraiswamy, 1996). Recently, Ko et al. (2005) showed that this calibration method could be extended to simulate the growth and lint yield of cotton by incorporating factors to calculate the appearance and growth of bolls. The procedure was demonstrated using cotton data from irrigated fields in the Texas High Plains. It was uncertain whether the model could accurately simulate the growth and yield of cotton experiencing water stress.

The measurements of actual crop growth used in within-season calibration can come from various sources. For example, ground-based field measurements of LAI or ground cover could be obtained at various times during the growing season for use in calibrating the model. However, obtaining ground-based measurements of these variables is often time consuming and labor intensive. Remote sensing, from ground-based spectroradiometers, airborne sensors, or satellites, can efficiently acquire data on crop canopy growth for numerous fields within an agricultural region. In some situations, the use of remotely sensed crop canopy data to calibrate a model can produce simulations of crop growth that are more accurate than those obtained using ground-based observations (Maas, 1993c).

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Abbreviations: BW, bandwidth; CWB, center waveband; DOY, day of year; GDD, growing degree days; LAI, leaf area index; MTVI, modified triangular vegetation index; NIR, near-infrared; OSAVI, optimized soil-adjusted vegetation index; PAR, photosynthetically active radiation; PVI, perpendicular vegetation index; VI, vegetation index.

The objectives of this study were (i) to demonstrate the ability of a model that uses within-season calibration to accurately simulate the growth and lint yield of cotton under a variety of water-stressed conditions and (ii) to compare different vegetation indices for their ability to calibrate the model to the measured field results. The vegetation indices have been suggested by other studies as being useful in evaluating cotton growth (Yang et al., 2001; Boydell and McBratney, 2002; Zarco-Tejada et al., 2005). The comparison was made to determine if some of the vegetation indices are more effective than others for within-season calibration of the model in simulating the growth and lint yield of cotton. The crop model simulations in this study were made using data collected independently of those used in developing the model.

MATERIALS AND METHODS

Verification Data

Cotton Field Data

The field study to verify the model was conducted at the USDA-ARS Plant Stress and Water Conservation Laboratory (33°35′38″ N, 101°54′04″ W; altitude 990 m) at Lubbock, TX, from 2002 to 2004. Cotton (Paymaster 2326 BG/RR) was planted on 13 May in 2002 and 2003 and on 14 May in 2004. Study plots (165 by 10 m) were planted in north–south rows spaced 1.0 m apart. The soil was an Amarillo fine sandy loam, 1 to 3% slope (soil survey of Lubbock County, TX, issued in 1979, USDA Soil Conserv. Serv.). Irrigation treatments were established using a BIOTIC system (Upchurch et al., 1996). In this approach, different irrigation levels are established by assigning different amounts of time from the onset of stress before irrigation is applied. The time delays used in this study were 2.5, 5.5, and 7.5 h in 2002 and 5.5, 6.5, 7.5, and 8.5 h in 2003 and 2004. Cotton yield of the 2.5-h treatment was not different from the 5.5-h treatment in 2002, even though more water was applied. Therefore, although three irrigation levels were established in 2002, four levels from 5.5 to 8.5 h were used in 2003 and 2004 to provide a range of water application within the deficit irrigation region. Irrigation was applied with a subsurface drip irrigation system with laterals installed 0.3 m below the surface of each bed (Wanjura et al., 2004).

A randomized, complete-block design was used with four replications of each irrigation level. Plants were sampled on day of year (DOY) 171, 191, 210, 226, and 254 in 2002; DOY 174, 190, 224, and 266 in 2003; and DOY 173, 194, 229, and 264 in 2004. Ten plants in each plot were randomly selected, cut, and transported to a laboratory where several plant growth parameters, including leaf area, were measured. Leaf area was measured using a LI-3100 area meter (LI-COR, Lincoln, NE). Leaf area index (LAI) was calculated as leaf area per plant divided by ground area per plant. At the end of the growing season, lint yield was determined by hand-harvesting randomly selected areas (or by harvesting rows using a cotton stripper) for the plots of each treatment.

Weather data for the field site from 2002 to 2004 were obtained from the PSWC Weather Station (http://www.lbk.ars.usda.gov/wewc/weather.htm) at Lubbock, TX. That station is approximately 200 m away from the site. During the growing season (roughly 13 May to 15 October), average photosynthetically active radiation (PAR) was 10.0 MJ m^{-2} d^{-1}, and rainfall was 191 mm in 2002; PAR was 9.4 MJ m^{-2} d^{-1}, and rainfall was 167 mm in 2003; and PAR was 9.2 MJ m^{-2} d^{-1}, and rainfall was 308 mm in 2004.

Remote Sensing Data

A hand-held multispectral radiometer (CROPSCAN, Rochester, MN) was used to measure the reflectance of each plot. It accommodates up to 16 bands to measure incident and reflected radiations. The center wavebands (CWB) and bandwidths (BW) for the 13 filters used in this study were CWB 460 nm with BW 10.0 nm, CWB 485 nm with BW 90.0 nm, CWB 500 nm with BW 40.0 nm, CWB 560 nm with BW 9.4 nm, CWB 600 nm with BW 10.1 nm, CWB 660 nm with BW 10.0 nm, CWB 700 nm with BW 12.3 nm, CWB 750 nm with BW 40.0 nm, CWB 800 nm with BW 65.0 nm, CWB 830 nm with BW 40.0 nm, CWB 880 nm with BW 12.4 nm, CWB 940 with BW 13.2 nm, and CWB 1100 nm with BW 16.5 nm. For calibration, a white standard card with known spectral reflectance with which to compare down sensor readings was used as a measurement reflectance. The measurement condition of the radiometer was a 15-degree field of view for reflected irradiation sensors and vertically 2 m in height above target areas. Reflectance was measured on DOY 206, 218, 220, 226, 240, 247, and 256 in 2002; DOY 136, 149, 174, 191, 195, 205, 219, 225, 233, 240, 254, and 269 in 2003; and DOY 135, 167, 183, 189, 196, 203, 216, 223, 236, 246, 253, and 267 in 2004. In each plot, reflectance was measured with five replications in three different locations. Measurements were made between 1100 h and 1300 h CDT on clear days but were delayed on some days with partial cloudiness to achieve measurement during clear-sky conditions.

Reflectance measurements were used to calculate the values of the five VI designs as described in Table 1. To calculate the perpendicular vegetation index (PVI), an equation for the bare soil line was obtained using measurements of near-infrared (NIR) and red reflectance made on bare soil at the field site (Richardson and Wiegand, 1977). The slope (1.24) and intercept (0.02) values presented in Fig. 1 were used as the coefficients a and b in the PVI equation (Table 1).

Validation Data

The field data set used to validate the model was collected from an experimental field at the USDA-ARS Plant Stress and Water Conservation Laboratory at Lubbock, TX, in 2005. This data set was separately obtained from the field data used for verification. The soil was an Amarillo fine sandy loam, 1 to 3% slope. Cotton variety Paymaster 2326 BG/RR was planted on 7 June. Study plots (165 by 10 m) were planted in north–south

Table 1. Vegetation indices used for leaf area index estimation.

Vegetation index	Equation†	Reference
Normalized difference vegetation index	$(R_{800} - R_{660})/(R_{800} + R_{660})$	Rouse et al. (1974)
Modified triangular vegetation index	$1.2(1.2[R_{800} - R_{560}] - 2.5[R_{660} - R_{560}])$	Haboudane et al. (2004)
Re-normalized difference vegetation index	$(R_{800} - R_{660})/\sqrt{R_{800} + R_{660}}$	Rougean and Breon (1995)
Optimized soil-adjusted vegetation index	$(1 + 0.16)(R_{800} - R_{660})/(R_{800} + R_{560} + 0.16)$	Rondeaux et al. (1996)
Perpendicular vegetation index	$(R_{800} - a \times R_{660} - b)/\sqrt{1 + a^2}$	Richardson and Wiegand (1977)

† R_{800}, R_{660}, and R_{560} represent the reflectance values of each waveband of 800, 660, and 560. The values of *a* and *b* in the perpendicular vegetation index equation are the slope and intercept from the linear equation of the bare soil line.

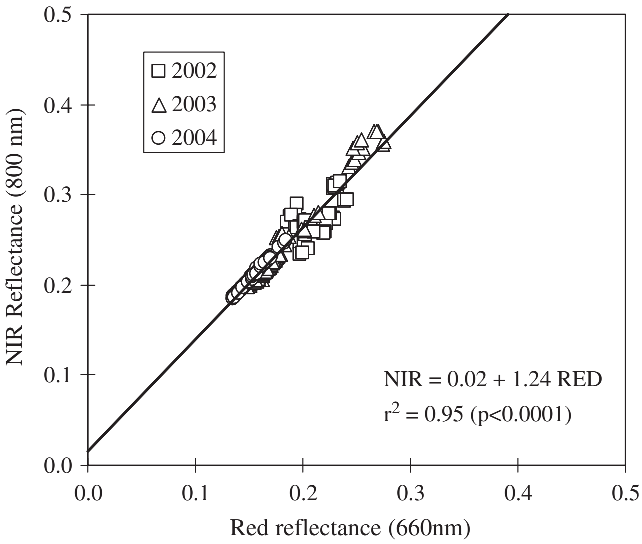

Fig. 1. The soil line determined from the linear relationship between near-infrared (NIR) and red reflectance of bare soils of 2002, 2003, and 2004 data (n = 432).

rows spaced 1.0 m apart. Irrigation was applied with a subsurface drip irrigation system with laterals installed 0.3 m below the surface of each bed. The irrigation treatments were 2, 4, 6, and 8 mm d^{-1}. The amounts of the accumulated irrigation and rainfall during the season were 358, 460, 562, and 664 mm, respectively. A randomized, complete-block design was used with four replications of each irrigation treatment. Plants were sampled on DOY 187, 206, 234, and 269 to measure leaf area and growth parameters. The hand-held CROPSCAN radiometer used for model verification was used to collect remotely sensed data. Reflectance of plant canopy was measured on DOY 164, 171, 179, 187, 192, 206, 214, 220, 229, 235, 242, 258, and 264. Lint yield was determined using hand harvesting. During the growing season (7 June–15 October), PAR was 9.5 MJ m^{-2} d^{-1}, and rainfall was 158.7 mm.

Model Revision and Simulation

A cotton crop model that uses remote sensing data (Ko et al., 2005) was used in this study. During each day of a simulated growing season, the model goes through five processes to simulate cotton growth (Fig. 2). These include (i) calculation of growing degree days (GDD), (ii) absorption of incident solar radiation by the crop canopy, (iii) production of new dry mass by the crop canopy and determination of boll production, (iv) determination of LAI partitioning of new dry mass, and (v) the conversion of model-generated LAI values to corresponding VI values using empirically derived functions. At the end of the simulated growing season, the model uses the within-season calibration procedures (Fig. 2) originally used in GRAMI, in which simulated crop growth (LAI or VI) is compared with the measured crop growth. If the simulated growth is sufficiently different from the measured growth, model parameter values are adjusted, and the crop simulation is repeated from the planting date. This process of model integration and comparison is repeated until the difference between simulated and measured growth is minimized. A simulated growth curve going through measured LAI values with a minimal error is shown in Fig. 3. As a result, this iterative method results in improved agreement between the simulation and the measurements. There are four parameters (L_0, a, b, c) that control crop growth in the model. The initial values of L_0, a, b, and c were 2 $\times$

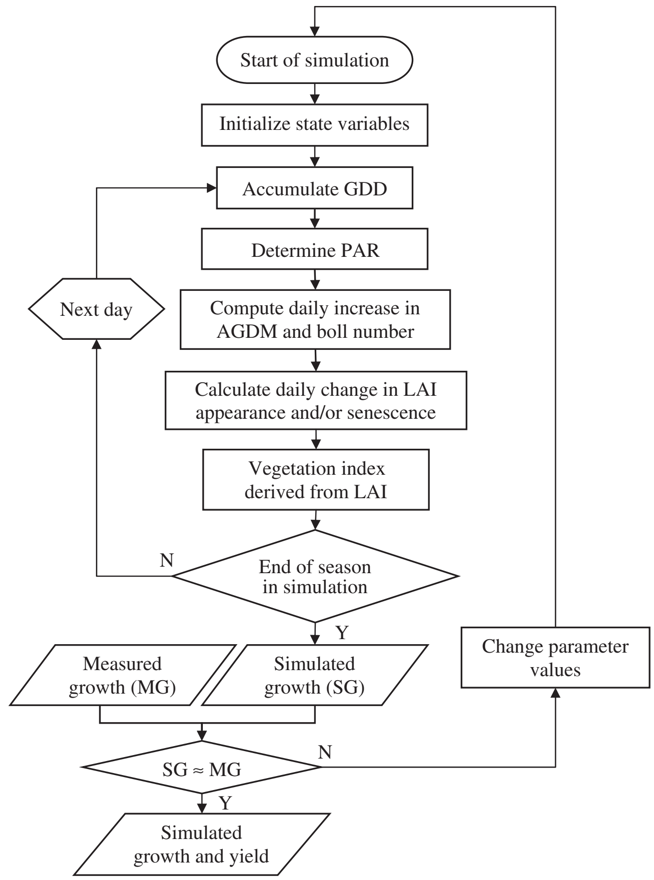

Fig. 2. Diagrammatic representation of the model that shows daily cotton growth processes and the within-season calibration (modified from Maas, 1993a and 1993b). Measured and simulated growths refer to measured and simulated leaf area index or vegetation indices. AGDM, above-ground dry mass; GDD, growing degree days; LAI, leaf area index; PAR, photosynthetically active radiation.

10^{-7}, 3.25×10^{-1}, and 1.25×10^{-3}. The initial value (L_0) of LAI at crop emergence is determined in the first step, followed by the parameters of a, b, and c in order in the model calibration. Details of these procedures were described by Maas (1993b).

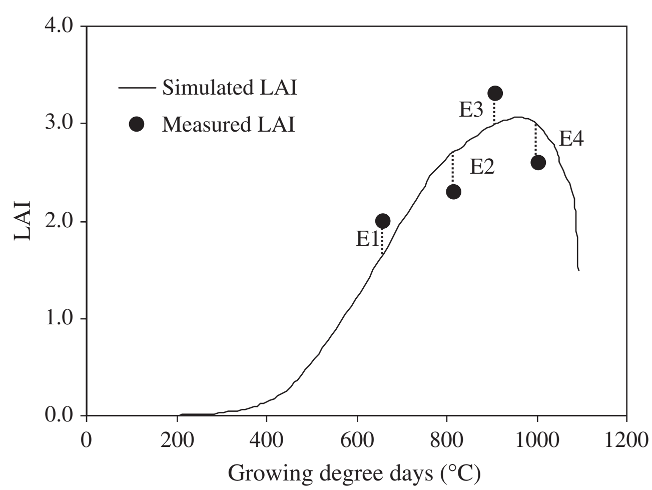

Fig. 3. An example of simulated leaf area index (LAI) passing through measured LAI values. The dotted lines (E1 to E4) represent the errors between simulated and measured values of LAI.

Because the previous cotton model was developed and tested under irrigated conditions, the model was revised to make it more applicable for water-stressed conditions. Lint yield estimation in the model is directly evaluated from boll production. The daily increase in boll number (ΔB) depends on GDD and LAI and is calculated using the following equation:

$$\Delta B = \gamma \Delta D[(\Delta L/\Delta D)/\lambda] \quad [1]$$

where γ is a coefficient of boll production, ΔD is daily change in GDD, ΔL is daily increase in LAI, and λ is a coefficient related to LAI that affects daily boll production. The γ (0.57 GDd^{-1}) and λ (0.0058 GDd^{-1}) values were previously determined using field data under irrigated conditions (Ko et al., 2005). When a plant experiences a stress such as soil moisture deficit, a primary plant response is to reduce its size to reduce transpiration and maintenance respiration. The within-season calibration procedure objectively establishes parameter values that result in a match between modeled and measured conditions. As a result, it allows the effects of factors influencing crop growth (e.g., water stress) to be implicitly incorporated into the simulation. Because boll number is a function of plant growth (Ko et al., 2005), the model assumes boll production is also reduced by stress factors. Because the γ value was determined from plants under well irrigated conditions, it needs to be adjusted for plants experiencing water stress. In the revised model, γ is reduced by 30% if the ΔL/ΔD value is less than λ, which is an indicator of water stress. This generally corresponds to the report by Kerby and Hake (1993), who reported that the low irrigation treatment (609.6 mm seasonal total) produced 74% as many fruiting positions as the moderate irrigation treatment (762 mm).

The model design includes provisions for including measured VI or LAI values as input for within-season calibration. To accomplish this, conversion functions (Table 2) were incorporated in this version of the model. The conversion functions for each VI design were derived from the 3 yr of field data. When measured VI values were plotted against the corresponding measured values of LAI, each data set could be adequately fit with a power function, showing that modeled VI values can be estimated as a power function of model-generated LAI. However, these equations might vary in other environments or regions because some results agree and others disagree with results from other studies (Lillesaeter, 1982; Sellers et al., 1986; Baret and Guyot, 1991; Richardson et al., 1992; Haboudane et al., 2004). It is assumed that saturation of VI values corresponding to higher LAI values varies among different study sites and different varieties. Additional studies are required to determine the degree to which these equations can be generally applied.

Model runs were independently conducted with VI inputs calculated from the index designs in Table 1 to test each design's suitability for within-season calibration. Simulated VI values were derived from the corresponding LAI to VI conversion function, and simulated LAI and lint yields were compared with the measured values of VI, LAI, and lint yields for each year and each irrigation treatment. Standard errors were calculated using the statistical and mathematical functions of Microsoft EXCEL. Other statistical analyses, such as RMSE, were calculated using SAS software (SAS version 8.1, SAS Institute, Cary, NC).

Table 2. Relationships between leaf area index (LAI) and the vegetation indices (VIs) using the 2002, 2003, and 2004 data (n = 41).

Relation between LAI and VIs†	r^2
NDVI = 0.47 $LAI^{0.42}$	0.86 ($P < 0.0001$)
RDVI = 0.34 $LAI^{0.47}$	0.86 ($p < 0.0001$)
OSAVI = 0.41 $LAI^{0.45}$	0.86 ($p < 0.0001$)
MTVI = 0.31 $LAI^{0.68}$	0.79 ($p < 0.0001$)
PVI = 0.10 $LAI^{0.79}$	0.83 ($p < 0.0001$)

† The VIs are normalized difference vegetation index (NDVI), renormalized difference vegetation index (RDVI), modified triangular vegetation index (MTVI), optimized soil-adjusted vegetation index (OSAVI), and perpendicular vegetation index (PVI).

RESULTS AND DISCUSSION

Remote Sensing

Reflectance in each waveband during the cotton growing season in 2003 and 2004 showed similar seasonal variation (Fig. 4). A comparable range of variation could not be determined in 2002 because reflectance measurements were available only after DOY 206. Reflectance in NIR region was highest on DOY 218 in 2002 and DOY 205 in 2003 and DOY 216 in 2004. There were large increases in reflectance in the NIR region after DOY 174 in 2003 and DOY 167 in 2004. It seems that seasonal variation of

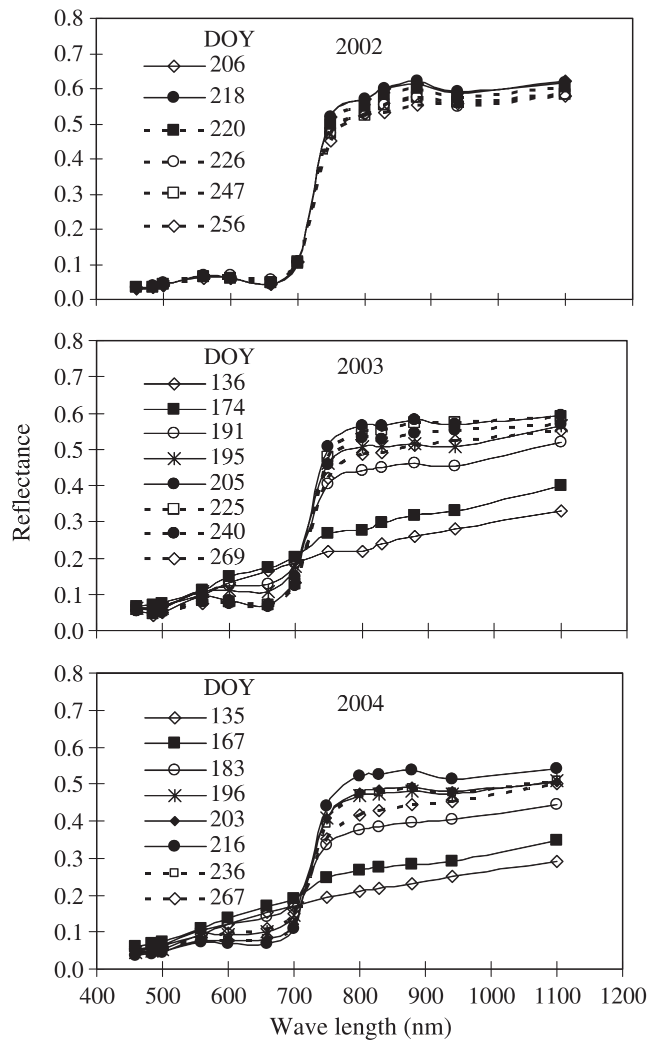

Fig. 4. Changes of average reflectance values for each waveband during crop growing season in 2002, 2003, and 2004. Measurements were made after day of year (DOY) 206 in 2002, and not all measurement dates are shown in 3 yr. Cotton was planted on DOY 133 in 2002 and 2003 and on DOY 134 in 2004.

cotton crop canopy could be qualitatively monitored using that of NIR reflectance. These results generally correspond to the seasonal variation of hyperspectral reflectance by Zarco-Tejada et al. (2005).

Differences of canopy reflectance among different treatments were also analyzed using the reflectance data on average of the seasonal measurements and at approximately maximum LAI (between DOY 210 and 220 in 2002, 2003, and 2004). Because the measurement dates were variable for the 3 yr, the data at approximately maximum LAI was used to see year-to-year variation as well. When reflectance was compared among the different irrigation treatments for each year, differences of canopy reflectance were noticeable in the wavebands from 750 to 940 nm (Fig. 5). Therefore, canopy variation due to different irrigation treatments could be qualitatively determined using the variation in NIR reflectance. Previously, Moran et al. (1989) reported that water-stressed canopies in alfalfa (*Medicago sativa* L.) have a lower spectral reflectance in the NIR and red wavebands when compared with unstressed canopies. Our results correspond to their results in the response to the reflectance of the NIR waveband. On the other hand, the variation of NIR reflectance was highest in 2004. It seems that the highest variation was influenced by the comparatively low reflectance of bare soil data in 2004 presented in Fig. 1. The difference in crop canopy among the 3 yr could not be determined using the difference in NIR reflectance. It is assumed that this was affected by the difference in bare soil reflectance among the 3 yr, which influences canopy reflectance.

Crop Modeling

Verification

The performance of the model iterative procedure was evaluated by comparing simulated values of the VI and LAI with the measured values of the VI and LAI for each irrigation treatment in 2002, 2003, and 2004 (Fig. 6). For all simulations involving the VI, simulated

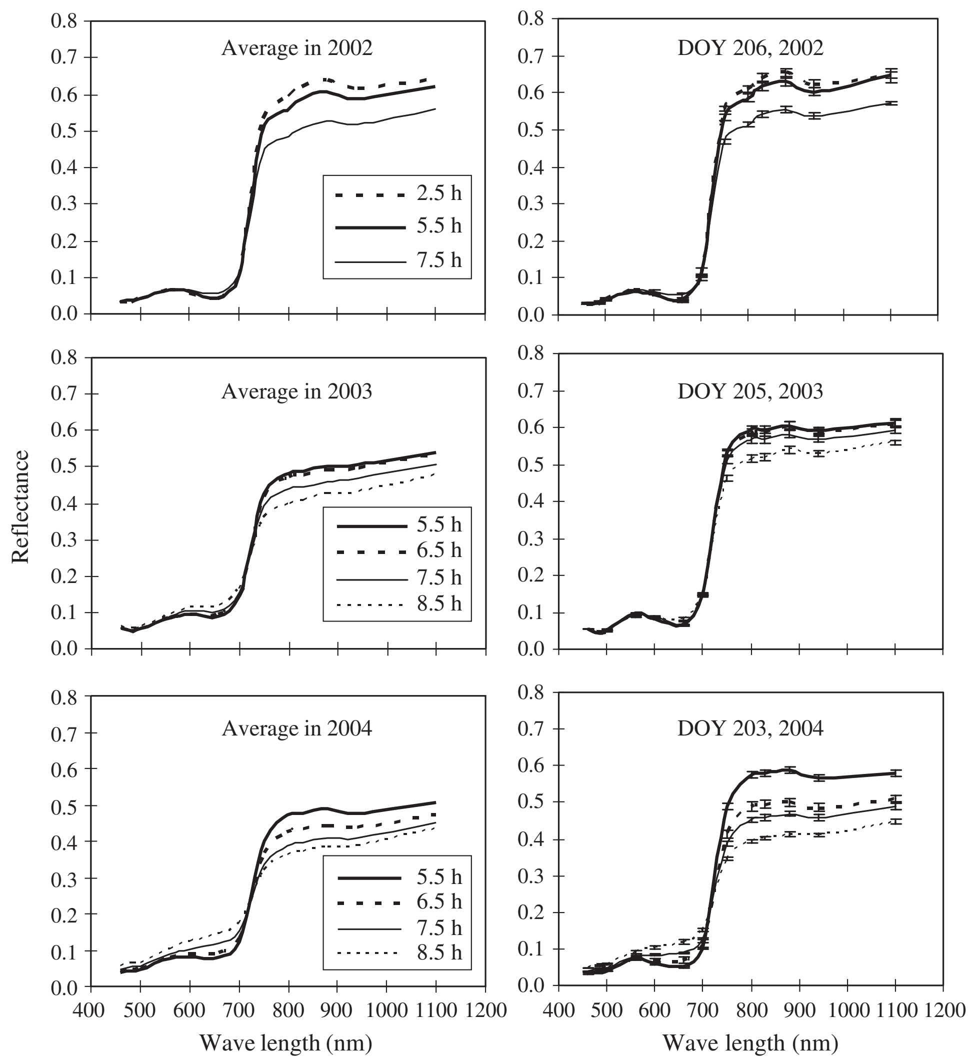

Fig. 5. Changes of reflectance for each waveband at the seasonal average (left) of measured data and at close to maximum leaf area index (right) as a function of different irrigation levels in 2002, 2003, and 2004. Vertical bars represent standard errors on the data points (for each treatment, $n = 49$ in 2002, $n = 36$ in 2003 and in 2004). Cotton was planted on day of year (DOY) 133 in 2002 and 2003 and on DOY 134 in 2004. LAI, leaf area index.

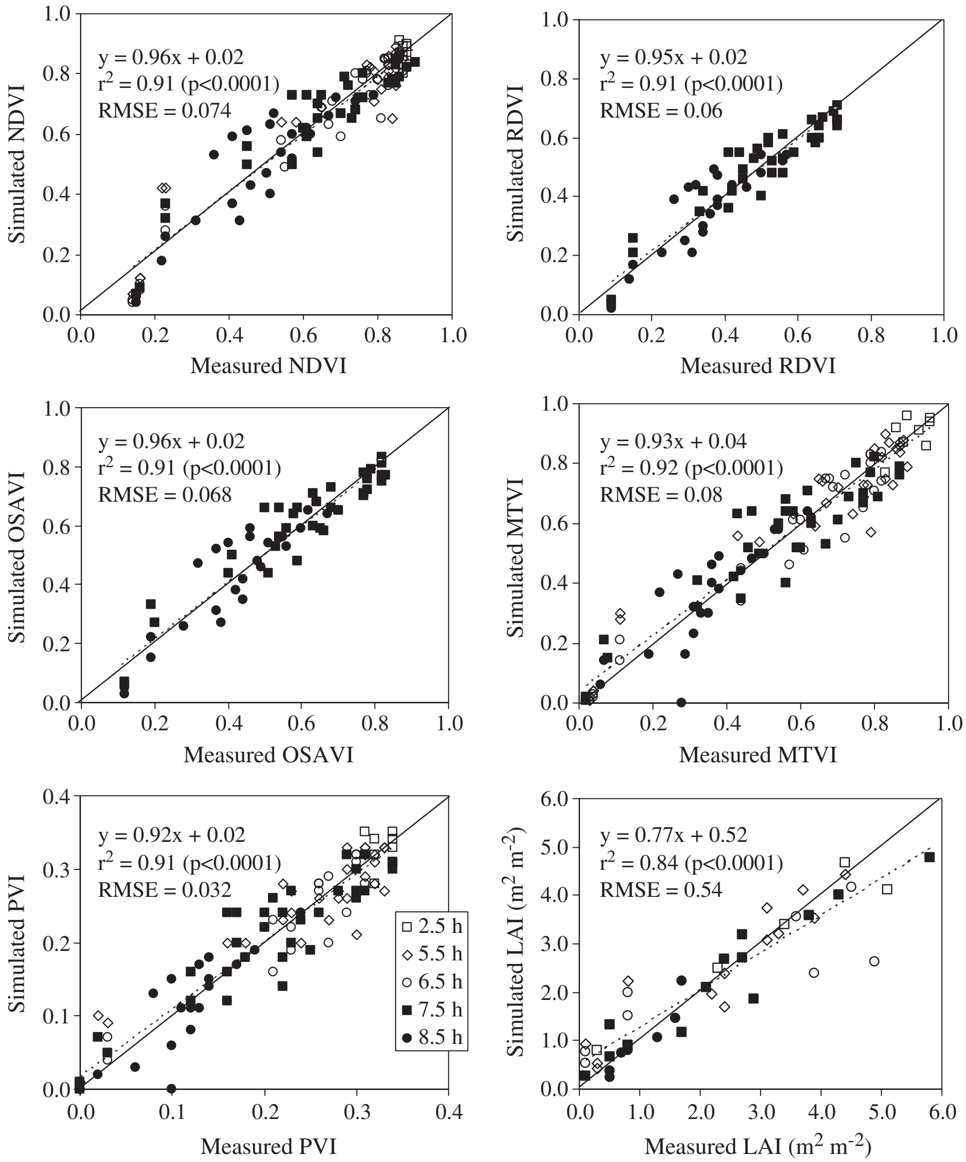

Fig. 6. Simulated vs. measured VI and LAI for different irrigation levels in 2002, 2003, and 2004. The solid diagonal line represents the ratio 1:1. The VI are normalized difference vegetation index (NDVI), re-normalized difference vegetation index (RDVI), modified triangular vegetation index (MTVI), optimized soil-adjusted vegetation index (OSAVI), and perpendicular vegetation index (PVI).

VI values were in agreement with the measured VI values equally well, whereas RMSE was smallest in simulation using PVI. Details for r^2 and RMSE values in the 3 yr were as follows: r^2 values for NDVI were 0.36 in 2002, 0.90 in 2003, and 0.89 in 2004, and RMSE values were 0.042 in 2002, 0.085 in 2003, and 0.077 in 2004; r^2 values for RDVI were 0.54 in 2002, 0.90 in 2003, and 0.90 in 2004, and RMSE values were 0.040 in 2002, 0.069 in 2003, and 0.060 in 2004; r^2 values for the optimized soil-adjusted vegetation index (OSAVI) were 0.48 in 2002, 0.90 in 2003, and 0.90 in 2004, and RMSE values were 0.041 in 2002, 0.080 in 2003, and 0.069 in 2004; r^2 values for modified triangular vegetation index (MTVI) were 0.71 in 2002, 0.89 in 2003, and 0.89 in 2004, and RMSE values were 0.058 in 2002, 0.091 in 2003, and 0.081 in 2004; r^2 values for PVI were 0.55 in 2002, 0.89 in 2003, and 0.91 in 2004, and RMSE values were 0.028 in 2002, 0.037 in 2003, and 0.030 in 2004; r^2 values for LAI were 0.91 in 2002, 0.72 in 2003, and 0.94 in 2004, and RMSE values were 0.43 in 2002, 0.69 in 2003, and 0.36 in 2004. Overall, simulated VI and LAI agreed with the measured VI and LAI in the 3 yr. The r^2 values in 2002 were smaller than the other years. It is believed that this was caused by data points concentrated on a range of values because the reflectance data in 2002 was available after DOY 206. Simulated VI shown here were obtained from the functions shown in Table 2, which were derived from the measured VI. Therefore, it is not surprising that there is good agreement between the measured and simulated values. Using this procedure, we demonstrate that the model incorporated with the functions can successfully reproduce the field condition of cotton leaf developments.

Simulated lint yields determined using the VI and LAI showed agreement with the measured lint yields, with r^2 of 0.57 and RMSE of 124.7 kg ha^{-1} for NDVI, r^2 of 0.62 and RMSE of 122.7 kg ha^{-1} for RDVI, r^2 of 0.60 and RMSE of 118.9 kg ha^{-1} for OSAVI, r^2 of 0.62 and RMSE of 122.0 kg ha^{-1} for MTVI, r^2 of 0.67 and RMSE of 99.3 kg ha^{-1} for PVI, and r^2 of 0.71 and RMSE of 100.1 kg ha^{-1} for LAI (Fig. 7). Most yield estimates were within 1 SE of the corresponding measured values for the 3 yr. The simulated lint yields of each treatment were in reasonable agreement with the measured lint yields. This suggests that the model could reproduce variations in lint yield, resulting from soil moisture deficit. Although RMSE (99.3) was the least in the simulation involving PVI, variations in r^2 and RMSE values among the simulations involving the other VI and LAI were small. Therefore, our results suggest that all VI used in the study seem to work equally well in calibrating the model.

Use of the within-season calibration procedure allows the factors influencing crop growth to be incorporated into the simulation. These factors can be genetic and environmental; examples include plant population, fertilization, and water stress. These are not only difficult to adequately incorporate into crop models but also increase the input requirements of them. Maas (1993a and 1993b) reported that a crop model capable of within-season calibration can adequately simulate crop growth and yield under various conditions. In this study, we demonstrate the possible extension of the within-season calibration procedure to assess lint yields under soil moisture deficit.

Validation

The accuracy of the model was tested using the independent data set obtained at Lubbock in 2005. Simulated VI and LAI were in agreement with measured VI and LAI for different irrigation treatments during the crop growing season (Fig. 8); r^2 and RMSE values were

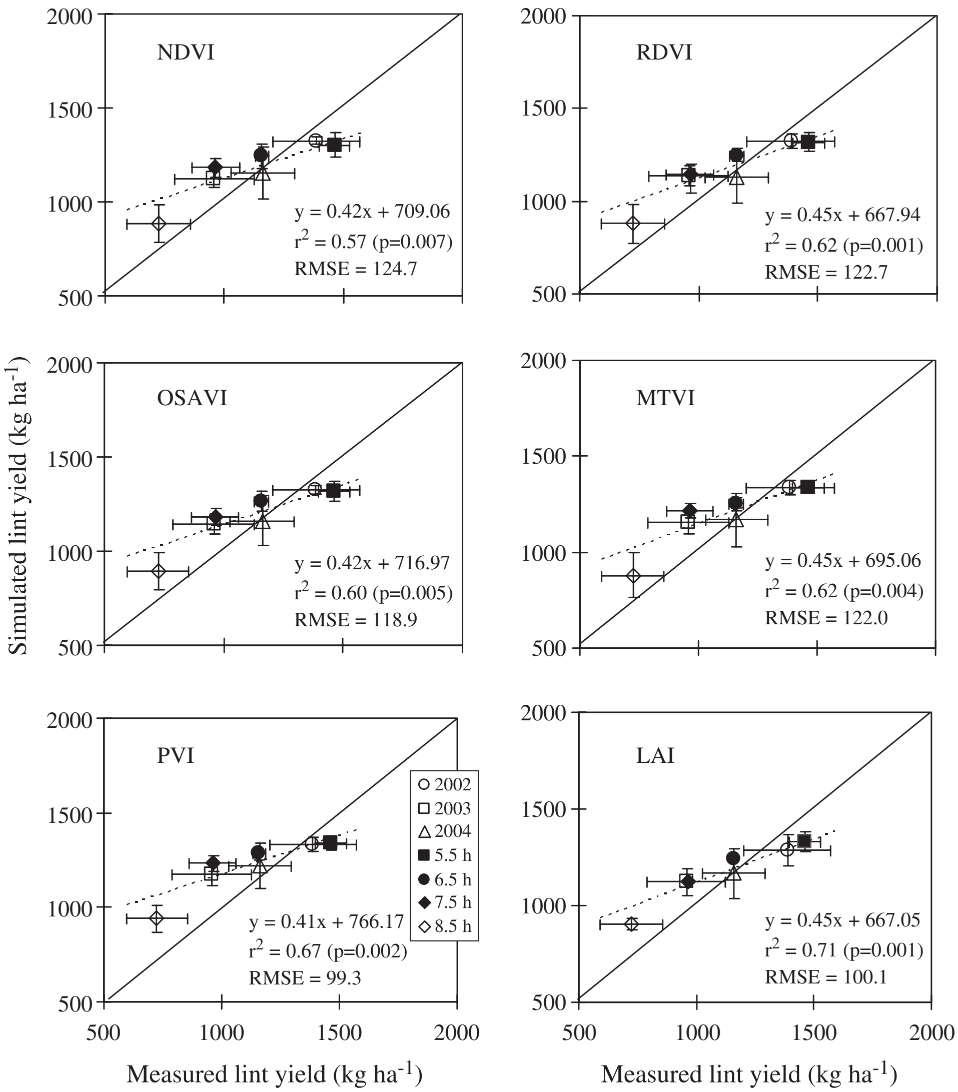

Fig. 7. Simulated vs. measured average lint yields for 3 yr and four irrigation levels data using five different vegetation indices (VI) and leaf area index (LAI). Vertical bars represent variation of the mean, and horizontal bars represent SE for observed values. The solid diagonal line represents the ratio 1:1. The VI are normalized difference vegetation index (NDVI), re-normalized difference vegetation index (RDVI), modified triangular vegetation index (MTVI), optimized soil-adjusted vegetation index (OSAVI), and perpendicular vegetation index (PVI).

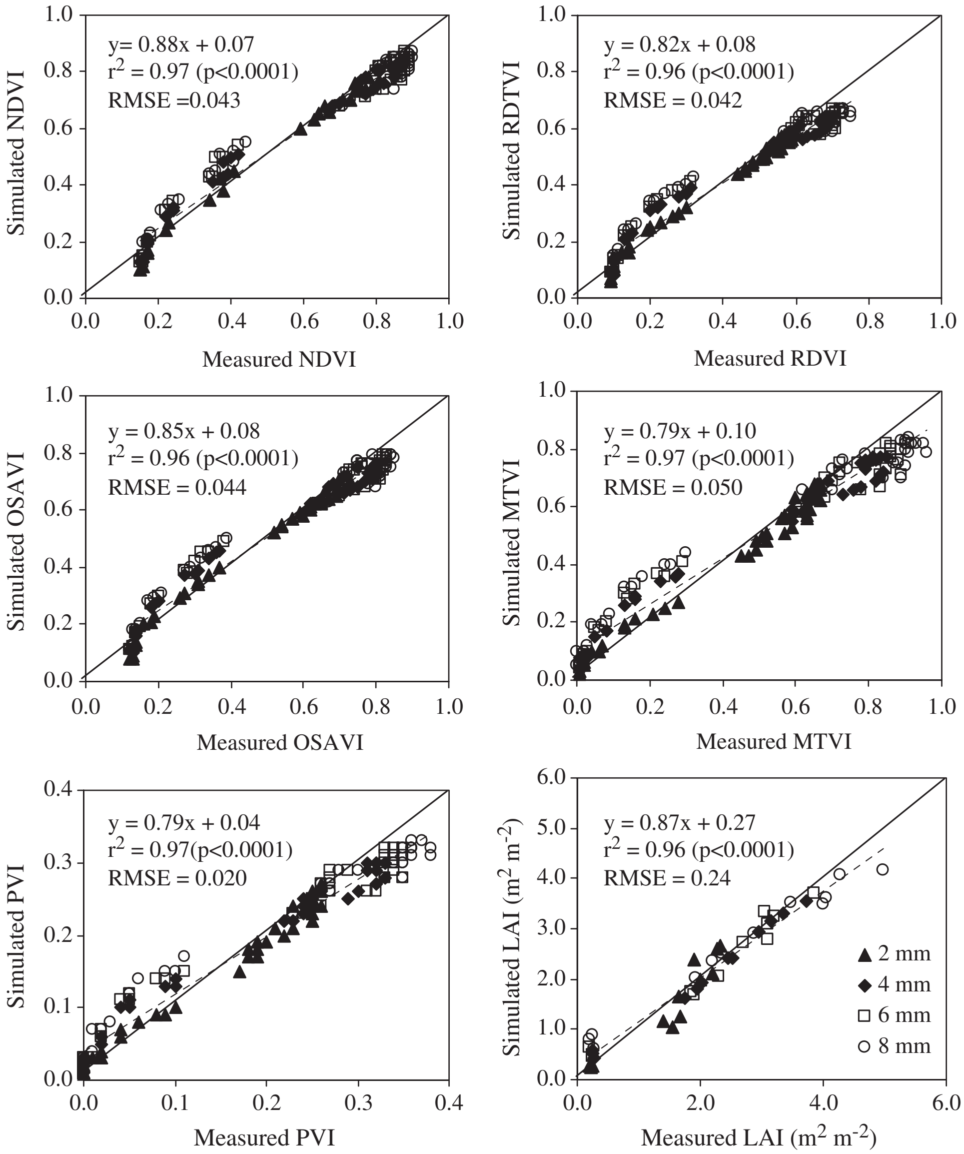

Fig. 8. Simulated vs. measured VI and LAI for different irrigation depths in 2005. The VI are normalized difference vegetation index (NDVI), renormalized difference vegetation index (RDVI), modified triangular vegetation index (MTVI), optimized soil-adjusted vegetation index (OSAVI), and perpendicular vegetation index (PVI).

0.97 and 0.042 for NDVI, 0.96 and 0.042 for RDVI, 0.96 and 0.044 for OSAVI, 0.97 and 0.050 for MTVI, 0.97 and 0.020 for PVI, and 0.96 and 0.24 for LAI. Simulated lint yields estimated using VI and LAI were in general agreement with the measured lint yields with r^2 of 0.63 and RMSE of 32.1 kg ha^{-1} for NDVI, R^2 of 0.66 and RMSE of 36.4 kg ha^{-1} for RDVI, r^2 of 0.67 and RMSE of 31.6 kg ha^{-1} for OSAVI, r^2 of 0.67 and RMSE of 40.9 kg ha^{-1} for MTVI, r^2 of 0.65 and RMSE of 28.3 kg ha^{-1} for PVI, and r^2 of 0.64 and 100.0 kg ha^{-1} for LAI (Fig. 9).

The results show that simulated lint yields involving the VI were somewhat underestimated in comparison with the measured lint yields after 1600 kg ha^{-1}. Polycarpic perennials generally reduce their partitioning to sexual reproduction under low availability of resources, such as water stress (Chiarello and Gulmon, 1991). Our model was designed to reduce the reproductive organs of cotton under soil moisture deficit conditions. However, the model was not very sensitive to the different irrigation treatments at the higher lint yields. It is assumed that canopy development was not different enough among the higher irrigation treatments to represent yield differences, whereas the model is sensitive to canopy development in estimating lint yield. Sanders et al. (1997), by contrast, reported that reproductive allocation of cotton was relatively stable in response to environmental factors. Other studies with cotton demonstrated that there is a reasonably stable relationship between final harvest index and environmental factors, including water availability (Constable and Hearn, 1981; Orgaz et al., 1992; Kimball and Mauney, 1993). There was statistically no significant difference among the measured lint yields from the irrigation treatments at 4, 6, and 8 mm (Fig. 9);

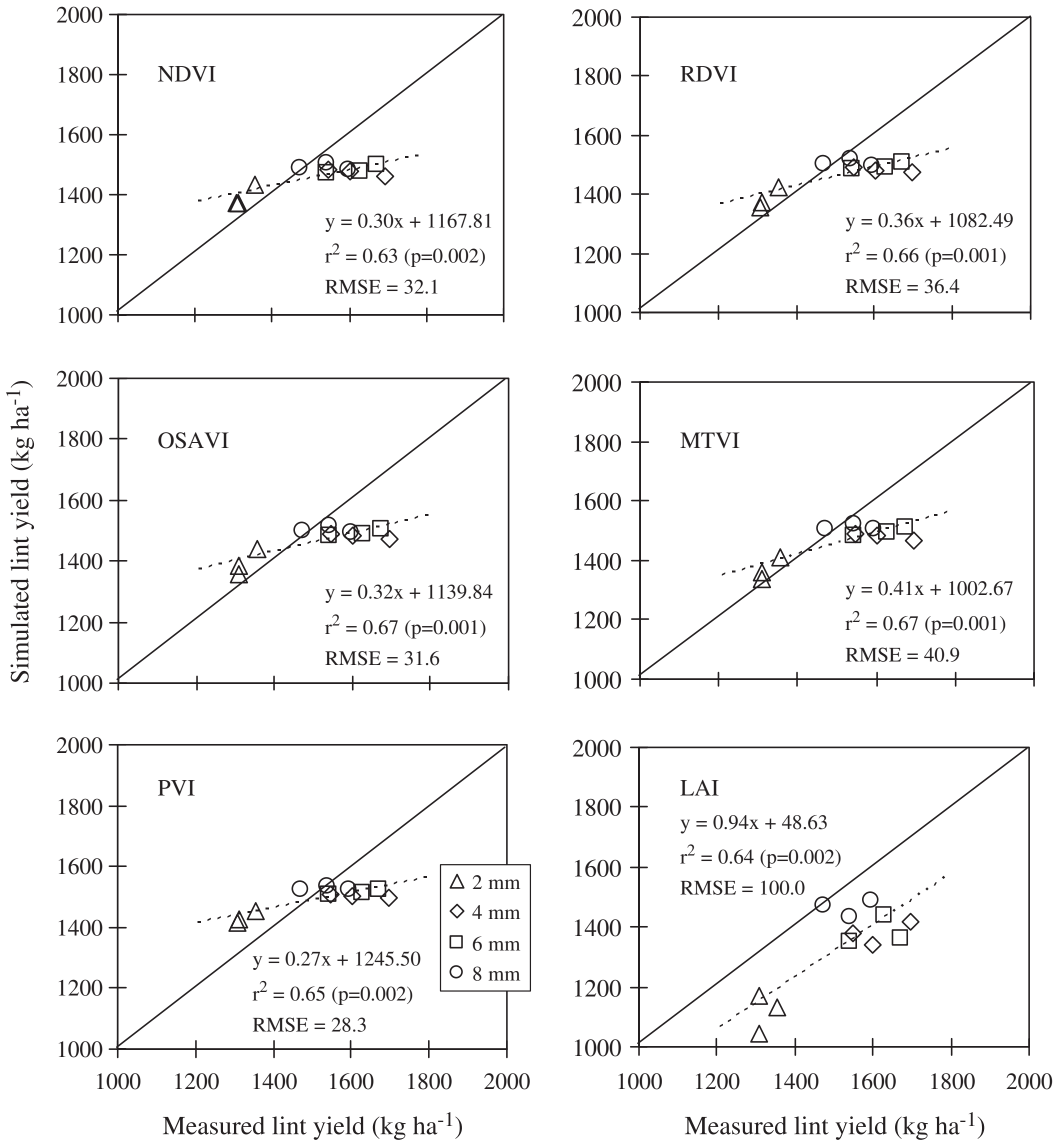

Fig. 9. Simulated vs. measured lint yields for four irrigation treatments using five different vegetation indices (VI) and leaf area index (LAI) in 2005. The solid diagonal line represents the ratio 1:1. The VI are normalized difference vegetation index (NDVI), re-normalized difference vegetation index (RDVI), modified triangular vegetation index (MTVI), optimized soil-adjusted vegetation index (OSAVI), and perpendicular vegetation index (PVI).

and SE values of the data points of 4 and 6 mm, respectively, lay at and close to the 1:1 ratio line. We believe that validation with more data sets is needed to deal with this matter. In addition, the previous studies (Ko, 2004; Maas and Doraiswamy, 1996; Moran et al., 1995) showed that simulation could agree more closely with measurement if data for within-season calibration occur at times critical to plant growth and development.

CONCLUSIONS

The revised model, previously modified from GRAMI to simulate cotton growth, demonstrated that the model can reproduce crop growth and lint yield under soil moisture deficit. Different VI values of interest, determined using a hand-held multispectral radiometer, were successfully used to calibrate the model using remote sensing data. When the VI and LAI were used as input values for within-season calibration, the model was able to simulate the effects of water stress on the cotton crop growth and lint yield. However, the validation result shows that the model was not very sensitive to the higher irrigation treatments in reproducing lint yield. Validation with more data sets is assumed to deal with this matter. The results showed that the five VI designs considered in this study worked equally well when used for within-season calibration. Thus, when supplied with remote sensing data, the model seems to be capable of simulating cotton growth and yield under a variety of environmental conditions.

REFERENCES

Arkin, G.F., C.L. Wiegand, and H. Huddleston. 1977. The future role of a crop model in large area yield estimation. p. 87–116. *In* Pro-

ceedings of the Crop Modeling Workshop. USDA-NOAA-EDIS-CEAS, Columbia, MO.
Baez-Gonzalez, A.D., P. Chen, M. Tiscareno-Lopez, and R. Srinivasan. 2002. Using satellite and field data with crop growth modeling to monitor and estimate corn yield in Mexico. Crop Sci. 42:1943–1949.
Barns, M.B., P.J. Pinter, Jr., B.A. Kimball, G.W. Wall, R.L. LaMorte, D.J. Husaker, F. Adamsen, S. Leavitt, T. Thompson, and J. Mathius. 1997. Modification of CERES-Wheat to accept leaf area index as an input variable. The 1997 ASAE Annual International Meeting Sponsored by ASAE, Minneapolis, MN. 10–14 Aug. 1997. ASABE, St. Joseph, MI.
Baret, F., and G. Guyot. 1991. Potentials and limits of vegetation indices for LAI and APAR assessment. Remote Sens. Environ. 35: 161–173.
Boydell, B., and A.B. McBratney. 2002. Identifying potential within-field management zones from cotton-yield estimates. Precis. Agric. 3:9–23.
Chiarello, N.R., and S.L. Gulmon. 1991. Stress effects on plant reproduction. p. 161–168. *In* H.A. Mooney et al. (ed.) Response of plants to multiple stresses. Academic Press, New York.
Constable, G.C., and A.B. Hearn. 1981. Irrigation of crops in a sub-humid environment: VI. Effect of irrigation and nitrogen fertilizer on growth, yield, and quality of cotton. Irrig. Sci. 3:17–28.
Haboudane, D., J.R. Miller, E. Pattey, P.J. Zarco-Tejada, and I. Strachan. 2004. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. Remote Sens. Environ. 90:337–352.
Kerby, T., and K. Hake. 1993. Monitoring cotton's growth. ANR publications. Univ. of California, Oakland.
Kimball, B.A., and J.R. Mauney. 1993. Response of cotton to varying CO_2, irrigation, and nitrogen: Yield and growth. Agron. J. 85:700–706.
Ko, J. 2004. Development of a cotton crop model that uses remote sensing data. Dissertation, Texas Tech Univ, Lubbock.
Ko, J., S.J. Maas, R.J. Lascano, and D. Wanjura. 2005. Modification of the GRAMI model for cotton. Agron. J. 97:1374–1379.
Lillesaeter, O. 1982. Spectral reflectance of partly transmitting leaves: Laboratory measurements and mathematical modeling. Remote Sens. Environ. 12:247–254.
Maas, S.J. 1992. GRAMI: A crop growth model that can use remotely sensed information. Publ. ARS-91. USDA, Washington, DC.
Maas, S.J. 1993a. Parameterized model of gramineous crop growth: I. Leaf area and dry mass simulation. Agron. J. 85:348–353.
Maas, S.J. 1993b. Parameterized model of gramineous crop growth: II. Within-season simulation calibration. Agron. J. 85:354–358.
Maas, S.J. 1993c. Within-season calibration of modeled wheat growth using remote sensing and field sampling. Agron. J. 85:669–672.
Maas, S.J., and G.F. Arkin. 1978. User's guide to SORGF: A dynamic grain sorghum growth model with feedback capacity. Research Center Program and Model Doc. 78-1. Texas Agric. Exp. Stn., College Station, TX.
Maas, S.J., and P.C. Doraiswamy. 1996. Integration of satellite data and model simulation in a GIS for monitoring regional evaporation and biomass production. Proc. of 3rd Int. Conf. on Integrating GIS and Environmental Modeling, Santa Fe, NM. 21–26 Jan. 2006 [CD-ROM]. The National Center for Geographic Information and Analysis, Santa Barbara, CA.
Moran, M.S., P.J. Pinter, Jr., B.E. Clothier, and S.G. Allen. 1989. Effect of water stress on the canopy architecture and spectral indices of irrigated alfalfa. Remote Sens. Environ. 29:251–261.
Moran, M.S., S.J. Maas, and P.J. Pinter, Jr. 1995. Combining remote sensing and modeling for estimating surface evaporation and biomass production. Remote Sens. Rev. 12:335–353.
Orgaz, F., L. Mateos, and E. Fereres. 1992. Season length and cultivar determine the optimum evapotranspiration deficit in cotton. Agron. J. 84:700–706.
Richardson, A.J., and C.L. Wiegand. 1977. Distinguishing vegetation from soil background information. Photogram. Eng. Remote Sens. 43:1541–1552.
Richardson, A.J., C.L. Wiegand, D.F. Wanjura, D. Dusek, and J.L. Steiner. 1992. Multisite analyses of spectral-biophysical data for sorghum. Remote Sens. Environ. 41:71–82.
Ritchie, J.T., and S. Otter. 1985. Description and performance of CERES-Wheat: A user-oriented wheat yield model. p. 159–175. *In* ARS Wheat Yield Project. ARS-38. National Technology Information Service, Springfield, VA.
Rondeaux, G., M. Steven, and F. Baret. 1996. Optimization of soil-adjusted vegetation indices. Remote Sens. Environ. 55:95–107.
Rosenthal, W.D., R.L. Vanderlip, B.S. Jackson, and G.F. Arkin. 1989. SORKAM: A grain sorghum crop growth model. MP-1969. Texas Agric. Exp. Stn., College Station, TX.
Rougean, J.-L., and F.M. Breon. 1995. Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. Remote Sens. Environ. 51:375–384.
Rouse, J.W., R.H. Haas, J.A. Schell, D.W. Deering, and J.C. Harlan. 1974. Monitoring the vernal advancements and retrogradation of natural vegetation. NASA/GSFC, Greenbelt, MD.
Sanders, V.O., M.P. Bange, and S.P. Milroy. 1997. Reproductive allocation of cotton in response to plant environmental factors. Ann. Bot. (Lond.) 80:75–81.
Sellers, P.J., Y. Mintz, Y.C. Sud, and A. Dalcher. 1986. A simple biosphere model (SiB) for use within general circulation models. J. Atmos. Sci. 43:505–531.
Upchurch, D.R., D.F. Wanjura, J.J. Burke, and J.R. Mahan. 1996. Biologically identified optimal temperature interactive console (BIOTIC) for managing irrigation. United States Patent No. 5539,637. 23 July, 1996.
Wanjura, D.F., D.R. Upchurch, and S. Maas. 2004. Spectral reflectance estimates of cotton biomass and yield. Proc. Beltwide Cotton Conf., San Antonio, TX. 7–9 Jan. 2004. National Cotton Council of America, Memphis, TN.
Wilkerson, G.G., J.W. Jones, K.J. Boot, and J.W. Mishoe. 1985. SOYGRO V5.0: Soybean crop growth and yield model. Technical Documentation, Univ. of Florida, Gainesville.
Yang, C., J.M. Bradford, and C.L. Wiegand. 2001. Airborne multispectral imagery for mapping variable growing conditions and yields of cotton, grain sorghum, and corn. Trans. ASAE 44:1983–1994.
Zarco-Tejada, P.J., S.L. Ustin, and M.L. Whiting. 2005. Temporal and spatial relationships between within-field yield variability in cotton and high-spatial hyperspectral remote sensing imagery. Agron. J. 97:641–653.